

## IDENTIFICATION OF A LANDMARK IN A ROENTGENOGRAPHIC CEPHALOGRAM BY EMPLOYING THE WAVELET NEURONS

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This paper describes an identification method of a landmark in a roentgenographic cephalogram by employing the input-correlated wavelet neurons. For the purpose of improvement of identification precision, a novel pattern matching method, named “*wavelet neuron matching (WNM)*,” is proposed in this paper. Furthermore, the “*weighted window*”, which is proposed in this paper, enables us to consider the orthodontists’ knowledge on local information as precisely as possible. The effectiveness and the validity of the proposed method have been verified by the experiments to identify a landmark called Menton.

### 1. Introduction

In the orthodontics, an analysis using roentgenographic cephalogram shown in Fig.1 is practiced as an important means of diagnosis. The cephalometric analysis always requires very highly precise measurements. The measurements depend on the subjective assessment of an observer to decide where each anatomical landmark is located, and a measurement error is induced(Ref. 1, 2).

The automatic identification of landmarks by employing template matching has been proposed in order to reduce the measurement error caused by the observer(Ref. 3, 4). In the template matching, however, the similarity is examined on the basis of the cumulative intensity difference, so that a matching with high precision cannot be achieved.

To cope with this problem, this paper proposes a novel pattern matching method employing the multi-input-correlated wavelet neurons, named wavelet neuron matching (WNM). The wavelet neuron exhibits very high ability of generalization. Furthermore, the wavelet neuron guarantees the global minimum.

In addition, this paper proposes the “*weighted*

*window*” for WNM. If the “*weighted window*” is defined reasonably, WNM can realize a local softmatching, which reflects the knowledge of orthodontists (experts of orthodontics).

In order to demonstrate the effectiveness of the proposed method, it is applied to the identification of a landmark, which is called Menton (Me), in a roentgenographic cephalogram. The experimental results are sufficient to show the validity of the proposed method.

### 2. Wavelet Neuron Matching

In this section, a novel pattern matching method named wavelet neuron matching (WNM) is discussed.

#### 2.1. *Multi-input-correlated wavelet neuron model*

The wavelet neuron (WN) of independent multiple inputs has been proposed by one of the authors in 1994(Ref. 5). This WN has high ability of generalization with a guarantee of the global minimum.



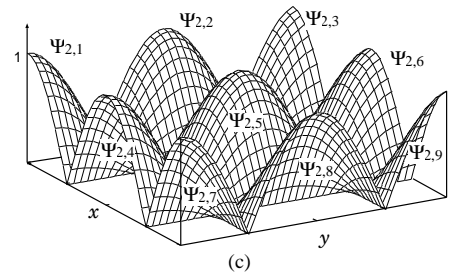
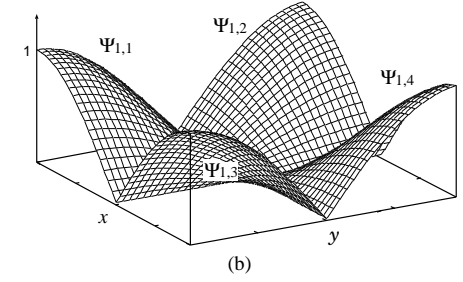
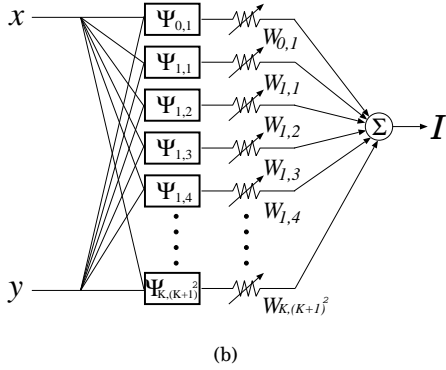
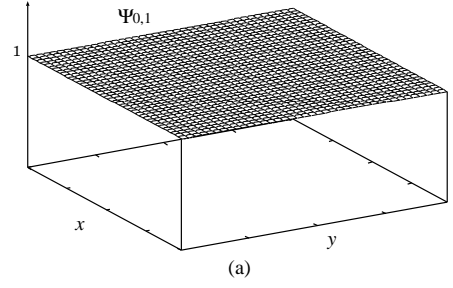
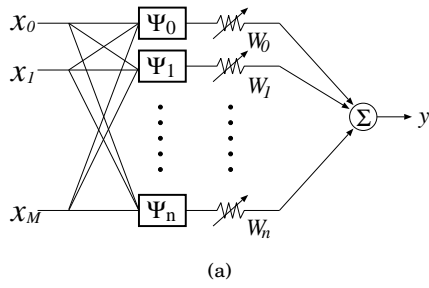


Fig. 2. Structure of the multi-input-correlated WN. (a)The general form of MIC-WN. (b)The two-input-correlated WN. (The simpler form of MIC-WN.)

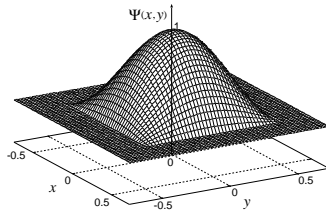


Fig. 3. The shape of a two-dimensional wavelet basis.

$(W_{0,1})$  represents the brightness of the input image.

### 2.3. Pattern matching employing MIC-WN

In this section, a novel pattern matching method, named wavelet neuron matching (WNM), is discussed.

A feature extraction is important for pattern matching. In the WNM, the weight vector of the MIC-WN is employed as the feature of an input image.

The soft-matching between two images which are similar to but different from each other is achieved by comparing two weight vectors,  $\mathbf{W}_a$  and  $\mathbf{W}_b$ , in two

Fig. 4. Arrangement of two-dimensional wavelet bases. (a)Level 0, (b)Level 1, (c)Level 2.

MIC-WNs as shown in Fig.6. These weight vectors are obtained by learning.  $\mathbf{W}_a$  and  $\mathbf{W}_b$  are compared with each other except level 0, since the weight of level 0 ( $W_{0,1}$ ) represents the brightness. The similarity  $S$  is obtained by the comparison.

As shown in Fig.5, the higher the level is, the more accurately the input image can be represented. Impulsive noise appears at very high level. In the proposed method, however, the weight vectors are compared at relatively low level. Therefore, it is effective to reduce the noise.

### 3. Application to the Identification of Landmarks in Roentgenographic Cephalogram

In this section, the way to apply the WNM to the identification of landmarks in roentgenographic cephalogram is discussed.

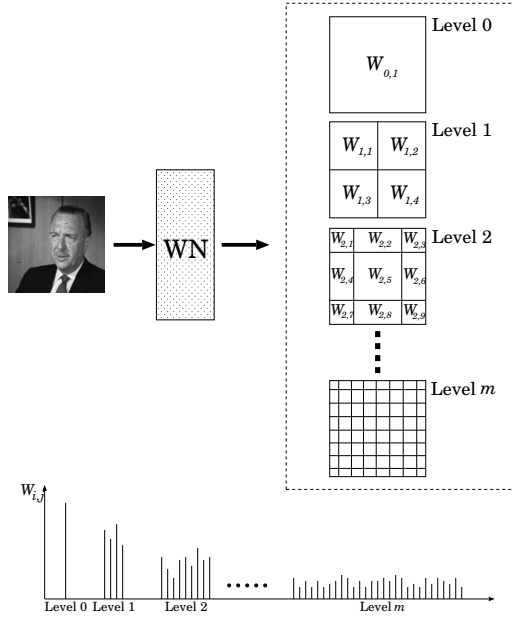


Fig. 5. The transformation from an image to a weight vector by the MIC-WN.

### 3.1. Template matching

In the conventional method for the identification of landmarks, the template matching has been employed. The correct coordinate of the target landmark in the template image is decided, in advance, by an orthodontist. The template image is shifted one pixel by one pixel on the test image, where the size of template image is sufficiently smaller than that of test image. In the template matching, the similarity is examined on the basis of a similarity measure, for example, Tanimoto Similarity Measure (Ref. 6); it is defined by following equation.

$$S_T(x, y) = \frac{(x, y)}{\|x\|^2 + \|y\|^2 - (x, y)}, \quad (5)$$

where  $x$  and  $y$  are intensities of the template and the test image, respectively.  $S_T(x, y)$  indicates 1 when the template and the test image are matched perfectly. The correct coordinate in the region which gives max  $S_T(x, y)$  is obtained as the identified coordinate.

### 3.2. Consideration for the knowledge of orthodontists

When orthodontists decide where each landmark is

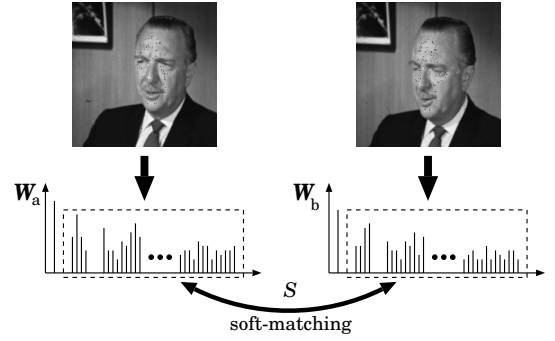


Fig. 6. The soft-matching between two different images by comparing two weight vectors,  $\mathbf{W}_a$  and  $\mathbf{W}_b$ , in two MIC-WNs.

located, their attention to the cephalogram changes locally. This is implemented by adopting the parameters  $\alpha_{i,j}$  which are assigned intuitively and construct the “weighted window” as shown Fig.7, which shows the case of Menton.  $\alpha_{i,j}$  ( $0 \leq \alpha_{i,j} \leq 1$ ) are the parameters which represent the importance of the  $j$ -th wavelet basis in the  $i$ -th level. A designer can weight each local position in the target region for matching process by assigning  $\alpha_{i,j}$ .

The knowledge of orthodontist can be considered by employing the similarity measure with the “weighted window.” This similarity measure is discussed in the next section.

### 3.3. Algorithm

The WNM is applied to the identification of landmarks in roentgenographic cephalogram as follows:

(step1) *Making of a template*

A cephalogram which is a standard craniofacial morphology is selected. A small region including the target landmark to identify is cut out of the cephalogram as a template image. The correct coordinate of the landmark in the template image is decided, in advance, by an orthodontist.

(step2) *Wavelet neuron matching (WNM)*

WNM is practiced as shown in Fig.8. The template image is transformed to the feature vector  $\mathbf{W}_t$  by one MIC-WN. An examined area in the test image, whose size is equal to as the template image, is transformed to the feature vector  $\mathbf{W}_o$  by another MIC-

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Fig. 7. The “weighted window” which represents the weighting parameters for each local region.

WN. An examined area is moved one pixel by one pixel. After the examination of similarity between  $\mathbf{W}_t$  and  $\mathbf{W}_o$  all over the test image, the area which indicates the max similarity is obtained as the most matching area.

The similarity is calculated by the following equations.

$$S_i = \frac{\sum_{j=1}^{(K+1)^2} \alpha_{i,j} (W_{t_{i,j}}, W_{o_{i,j}})}{(K+1)^2 \sum_{j=1} \alpha_{i,j} (\|W_{t_{i,j}}\|^2 + \|W_{o_{i,j}}\|^2 - (W_{t_{i,j}}, W_{o_{i,j}}))}, \quad (6)$$

where  $\alpha_{i,j}$  are the “weighted window” mentioned in the previous section. Similarity measure  $S_i$  in each level are summed up to produce the resultant similarity measure  $S$  as Eq.(7).

$$S = \sum_{i=1}^K S_i. \quad (7)$$

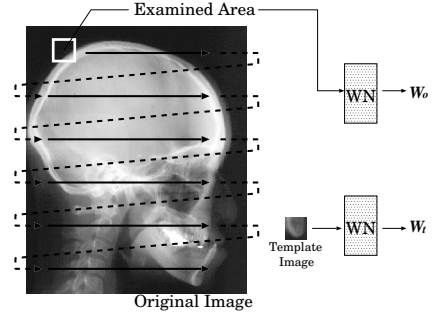


Fig. 8. The matching process of WNM.

(step3) *Identification of the target landmark*

The correct coordinate in the area of the biggest matching area which indicates the maximum similarity measure is given as the identified coordinate by WNM.

#### 4. Experimental Results

In order to demonstrate the effectiveness and the validity of the proposed method, it is applied to the automatic identification of a landmark called Menton (Me) in the practical cephalogram. In the experiments, the 256-level gray-scale digital images transformed from 23 roentgenographic cephalograms by using an image scanner are employed as image data. One cephalogram which is a standard craniofacial morphology around Me are selected as the template. The size of the template and the 22 test images is  $50 \times 50$  pixels and  $150 \times 150$  pixels, respectively. The correct coordinate of Me is decided, in advance, by an orthodontist on the display.

The following three methods are employed for comparison.

- (i) Template matching (TM)  
This template matching employs Tanimoto Similarity Measure as a similarity measure.
- (ii) WNM without the “weighted window” (WNM1)  
This is attempted in order to show the efficiency of WNM. In Eqs.(6) and (7),  $\alpha_{i,j} = 1, K = 6$ .
- (iii) WNM with the “weighted window” (WNM2)  
This is examined in order to show the validity of the “weighted window”. In Eqs.(6) and (7),  $K = 6$  and the values of  $\alpha_{i,j}$  are shown in Fig.7.

The experimental results are shown in Fig.9. These bar graphs show the distribution of error in distance in each matching method. The errors in distance of the proposed methods (WNM1 and WNM2) are smaller than that of the conventional method. Table1 shows “rate of correct identification (RCI)” in each method, where, “RCI” represents a percentage of test images whose errors in distance are calculated to be within 1mm. This accuracy is acceptable to orthodontists.

A variety of test images in craniofacial morphology are employed in the experiments. The proposed method, however, achieved the identification with relatively high precision.

Table 1. Rate of correct identification (RCI).

Method	TM	WNM1	WNM2
RCI	4.5	22.7	40.9

## 5. Conclusions

In this paper, a novel pattern matching method is proposed. The method is the local soft-matching employing the wavelet neurons. The local soft-matching is achieved by defining the “*weighted window*” which represents the weighting parameters for each local region in the target image.

In order to demonstrate the effectiveness of the proposed method, it was applied to the identification of a landmark called Menton. Experimental results show that the proposed method exhibited ten times higher precision in comparison with the conventional method.

## Acknowledgments

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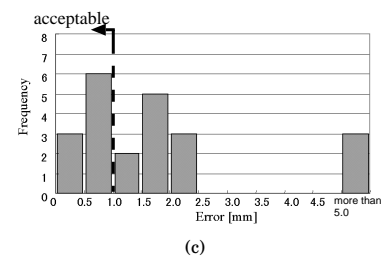
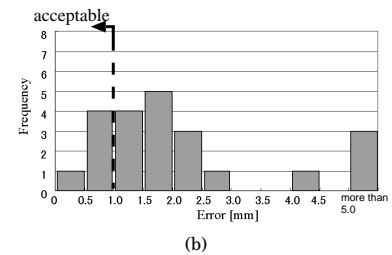
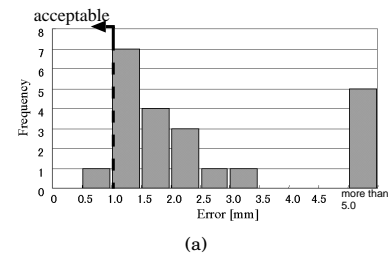


Fig. 9. The distribution of errors in distance for each method. (a)Template matching. (b)WNM without the “*weighted window*.” (c)WNM with the “*weighted window*.”

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